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Field Trial of Monitoring On-Demand at Intermediate-Nodes Through Bayesian Optimization

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Abstract: We demonstrate an intelligent monitoring on-demand switching strategy at network nodes based on Bayesian optimization. It is shown that our proposed method achieves identical monitoring capability as complete system exploration while saving a lot of data.

OCIS codes: (060.1155) All-optical networks; (060.4256) Networks optimization

1. Introduction

Traditional network planning tools estimate quality-of-transmission (QoT) with static Q factor models which are functions of the physical layer impairments (PLIs). These PLIs require complex computations, time-consuming measurements and expensive equipment that take considerable human effort and lack self-adaptiveness[1]. A solution to this problem is optical performance monitoring (OPM)[1][2]. Most OPM schemes retrieve information from the receiver node which only represents QoT at per lightpath level rather than per link level. An “in-depth” OPM scheme is demonstrated in [2] to retrieve monitoring data from both intermediate and receiver nodes to assess link-level optical-signal-to-noise-ratio (OSNR) performance, the monitoring data is further orchestrated by upper-layer algorithms to functionalize dynamic network planning. Whilst this solution proves effective, the booming data volume arising from the ubiquitous monitoring devices across the network becomes a serious problem. It is reported in [3] that the performance of software-defined networking (SDN) controller can suffer significant degradation by the rapid and frequent flow table update requests as well as big data transmission and processing. Instead of utilising big data analytics to select, classify and compute the target information at the later stage, it is data-efficient to prevent redundant information from the very early stage. From the perspective of optical networking, noise performance depends on amplifier noise figure, channel power, fiber loss, loading, etc. which vary significantly from channel to channel under system uncertainties, hence forming a “black box”. In this case, to design a protective and proactive network with “just enough” information, instead of exploring the whole “black box”, operators are more interested in learning the worst case link noise behaviour against wavelength with as few monitoring trials as possible.

In this paper, we propose and experimentally demonstrate a monitoring on-demand (MoD) switching strategy at intermediate nodes to eliminate redundant OPM data from the physical devices. Through learning of the existing channel performance and on-demand hardware switching[4], MoD retrieves key OSNR information with up to 91% data saving and significant time saving than other strategies, which enables an agile monitoring process.

2. Monitoring on-demand switching strategy

As OSNR information can only be retrieved on the basis of one channel each time[2], the monitoring device has to be shared among many channels at the intermediate nodes. The switching strategy/control algorithm of MoD comprises of two key steps: Gaussian process (GP) and Bayesian optimization (BO). A decision being made to switch to the next monitoring point(λ_{t+1}) is learned from the performances been monitored so far. Fig.1 shows the flow chart of the overall learning model. Specifically, in step (iii), GP regression for OSNR degradation ($OSNR_{de}$) vs λ is fitted to the existing monitoring data. For link i connecting node j and $j+1$, $OSNR_{de}^{link i} = OSNR_{node j} - OSNR_{node j+1}$. “Squared exponential” is used as the similarity kernel function[5] which measures how similar two points are correlated to each other, i.e. given the same lightpath, the OSNR degradations of two neighboring channels should be identical. GP samples functions for $OSNR_{de}$ vs λ given the training set, the prediction uncertainty region goes high given there is less training data (high variance) hence is more explorative. However, since we are only interested in the worst case OSNR performance, i.e. the global maxima point of $OSNR_{de}$ per link, the region around the monitored high $OSNR_{de}$ values (high mean) is likely to be improved, hence is more exploitative. To fit BO in step (iv), an acquisition function “probability of improvement” (GP-PI)[5] is used to cope with this fundamental exploration-exploitation trade-off. Fig. 2(a) shows the BO fitting pseudocode. GP-PI computes the probability of selecting the next monitoring point as: $u_{PI}(\lambda; D_n) := \Pr[OSNR(\lambda) > \mu_{OSNR}^+] = \Phi[(\mu_n(\lambda) - \mu_{OSNR}^+)/\sigma_n(\lambda)]$, μ_{OSNR}^+ is the worst (the highest) $OSNR_{de}$ value been monitored so far, $\mu_n(\lambda)$ and $\sigma_n(\lambda)$ are the posterior $OSNR_{de}$ mean

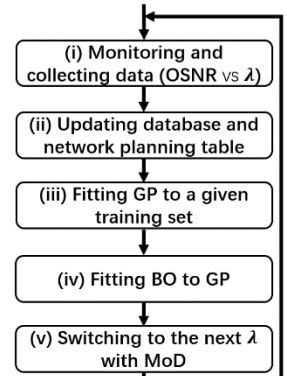


Fig. 1 overall learning flow chart

(exploitation) and standard deviation (exploration) of the next potential trial, Φ is the standard cumulative distribution function. GP-PI returns the area under the posterior Gaussian distribution above μ_{OSNR}^+ , the larger the area, the higher probability of improvement. BO process returns the next optimized monitoring choice λ_t by maximizing u_{PI} (maximum likelihood). After knowing which channel to monitor next, step (v) triggers MoD to switch the monitoring device to the next wavelength, as illustrated in Fig. 2(b). All the hardware devices are pre-connected in the optical fiber switch, including amplifiers, filters, couplers, etc. The input power is tapped and goes into the wavelength selective switch (WSS), OSNR monitoring is performed after filtering the wanted channel λ_t . The in-band OSNR monitoring function is pre-calibrated and implemented in the high-resolution (180MHz bandwidth) spectrum analyzer - Finisar WaveAnalyzer (WA) with 0.6dB OSNR monitoring error (QPSK) relative to out-of-band method[2]. The monitoring data is uploaded to a database for dynamic network planning and protection.

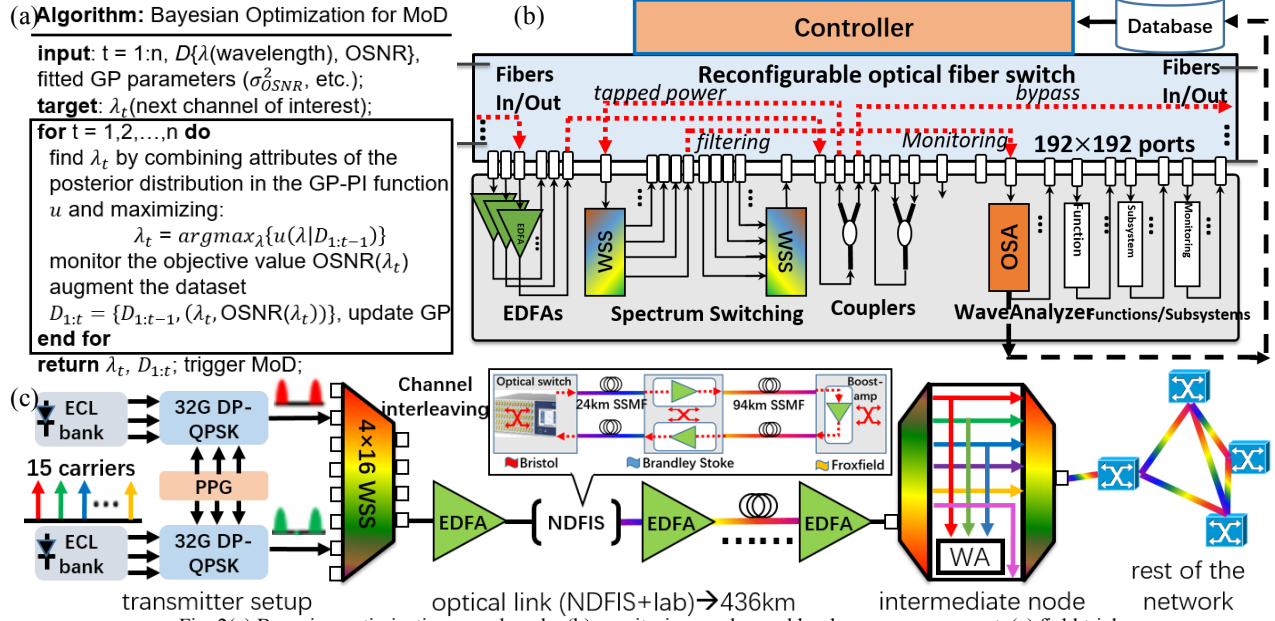


Fig. 2(a) Bayesian optimization pseudocode, (b) monitoring on-demand hardware cross-connect, (c) field trial testbed with NDFIS. ECL(external cavity laser), PPG(pulse pattern generator), DP-QPSK(dual polarization quadrature phase shift keying), EDFA(Erbium-doped fiber amplifier), SSMF(standard single mode fiber)

3. Field trial testbed and results

Fig. 2(c) shows the field trial network using part of the UK's National Dark Fiber Infrastructure Service (NDFIS) which allows experiments to be carried out in a real-world operating condition. 16 equalized 50GHz-spaced 32Gbaud DP-QPSK signals are generated at the transmitter side and launched into the network, channel power is amplified to 0 dBm/channel/span by each EDFA to avoid unwanted nonlinear distortion. Signals first enter the NDFIS loop-back link running from Bristol to Brandley Stoke and further to Froxfield which gives 236km effective transmission distance. Another 200km fiber link (lab-based) is connected after the loop-back (giving 436km in total) where signals are amplified every 50km. Launch OSNR is kept to 30dB by coupling additional noise to all the 16 channels to reduce computational complexity. Channel OSNRs undergo different degradations after the link, as shown in Fig. 3. We treat the transmitter as the previous node, MoD is performed in the intermediate node where signals pass WSS (add-drop), coupler (tapping power), filter (selecting the channel of interest), and enter WA for in-band OSNR monitoring.

Our target is to find $\max [OSNR_{de}^{link i}]$ which is equal to finding $\max [30dB - OSNR_{node j+1}]$ given $OSNR_{node j}$ is 30dB. Wavelength is indexed into 1 to 81 representing 191850GHz to 195850GHz at 50GHz grid. Fig. 4(a)-(c) show different decisions made for MoD depending on the normalized acquisition function u_{PI} , the estimation uncertainty (95% confidence integral) goes high where there is no training data, and vice versa. the next channel of interest λ_{next} is marked with stars in the figure. In Fig. 4(a), when there are only two training sets, the BO algorithm tends to be more explorative, the next best point is located where the GP uncertainty is the highest. After 4 points are monitored in Fig. 4(b), the decision is made to exploit the area with high means according to GP. The same applies to Fig.

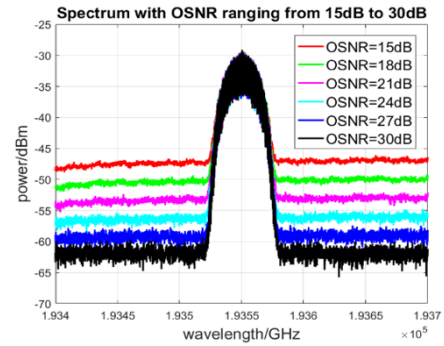


Fig. 3 OSNR degradation spectra

4(c)(exploitation). As more and more data are monitored and fed into BO algorithm, the decision made on λ_{next} will be fixed around the global maxima of the GP. As is shown in Fig. 4(d), two other switching strategies are used to assess the performance of MoD. 1. Sequential monitoring (SM): sequentially switching to each channel in the link from left to right. 2. Random monitoring (RM): switching is random. With a total number of 40 switching times, BO first finds the highest OSNR degradation locating at $\lambda = 194650\text{GHz}$ with 8 switching times, 62.5% quicker than SM (13 times) and 400% quicker than RM(40 times). 75% of the BO data is constant in retrieving the worst OSNR degradation (11dB) which means after the first detection, the rest of the data can be omitted, resulting in 50% data saving (8 channels out of 16). As BO is intrinsically confident in knowing λ_{next} to be the channel with the worse OSNR performance, there is no need to monitor all the channels while other methods have to. Fig. 4(e) demonstrates this confidence. The complete link OSNR performance is tested and recorded as reference value. Only 8 monitoring data is needed for MoD, the fitted GP curve has the posterior global maxima at exactly the same point as using all the 16 training channels (capturing most of the reference data), with 0.5dB prediction error relative to the reference value. This proves the capability of MoD in retrieving the most critical OSNR information with up to 91% data saving (8 out of 88 if C band fully loaded) while retaining identical prediction accuracy when deriving the whole “black box”.

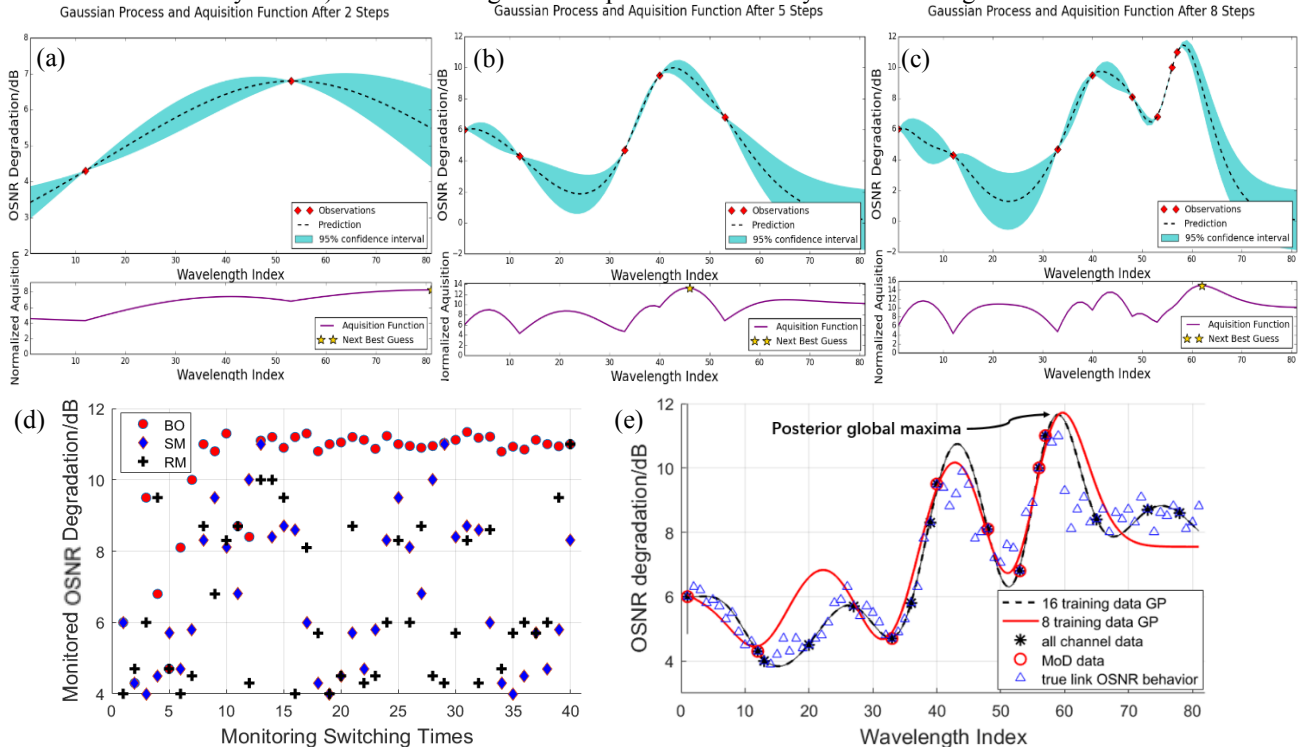


Fig. 4(a) GP fitting and acquisition function with 2 monitoring points, (b) with 5 monitoring points, (c) with 8 monitoring points, (d) monitoring data retrieved using BO, SM and RM, (e) prediction of global maxima $OSNR_{de}$ with MoD (8 data set) and complete GP fitting (16 test sets).

4. Conclusion

In this field trial we proposed and experimentally demonstrated a monitoring on-demand function at network nodes which monitors intermediate-node OSNR performance with intelligent switching strategy. With Bayesian optimization on top of Gaussian processes, MoD saves up to 91% of the monitoring data while accurately predicting the worst OSNR performance of the link with as few monitoring trials as possible. This capability enables a self-learning “out-of-the-loop” monitoring process and potentially eliminates big data issues in SDN.

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